Heliyon 9 (2023) e12943

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Research article

Iot application for energy poverty detection based on thermal comfort monitoring

Ascensión López-Vargas [*], Agapito Ledezma-Espino

Control Learning and Optimization Group, Computer Science and Engineering Department, University Carlos III of Madrid. Leganes, Madrid, Spain

ARTICLE INFO

Keywords:
Internet of things
Fuel poverty
Energy poverty
Sensors
Thermal comfort
Monitoring

ABSTRACT

The development of a datalogger for identifying Energy Poverty (EP) using thermal comfort monitoring is described in this work. There is not a uniform definition of EP, and no global recommendations indicating the thermal comfort characteristics that should be utilized to identify EP. Most Internet of Things (IoT)-based systems designed for EP identification measure energy consumptions (electricity and gas). There is a lack of works that use IoT-based systems to identify EP through the monitoring of thermal comfort parameters. To address the deficiencies discovered in the identification of EP from the perspective of thermal efficiency, an IoT-based monitoring system was designed, developed, and tested. A first pilot was installed in a household in Getafe. A full month of temperature, relative humidity, and CO_2 concentration measurements were utilized to evaluate the system, which was then compared to a commercial system. The results revealed that the new IoT-based approach was very dependable and may be used to accurately monitor EP-related parameters.

1. Introduction

There is no universally accepted definition of Energy Poverty (EP); however, it is commonly defined as the "*inability to keep adequate levels of heating, cooling and lighting*" in homes [1]. According to estimates from the European Union (EU) Energy Poverty Observatory [2], EP impacts more than 50 million homes across the European Union. Fig. 1 depicts the percentage of EU citizens that were unable to keep their homes warm enough in 2020. The EP circumstance within the European Nations changes: the most noteworthy rate of EP was come to in Bulgaria (27%). By contrast, Austria, Finland, Czechia, and the Netherlands showed the lowest EP rates (less than 2%). According to projections, the number of energy poor people in Europe will continue to rise because of recent occurrences such as the COVID-19 pandemic and the Russo-Ukrainian conflict [3,4].

The European Commission's Policy Report "*Energy poverty and vulnerable consumers in the energy sector across the EU: analysis of policies and measures*" [6] published in 2015 evaluated how European Member States characterize the EP and vulnerable consumers, as well as the measures put in place to address the issue. As this document indicates, there are three key factors that define EP (in combination or isolation): low-income, high energy prices, and poor building thermal efficiency. Quantifying energy poverty at the household level requires a large amount of data, and the lack of a uniform definition and methodology for measuring it across EU countries adds to the problem's complexity. Recent studies demonstrated that IoT-based dataloggers allows to measure and quantify the inequality of household energy behaviors and to identify hidden inequalities as well [7].

* Corresponding author.
E-mail address: aslopezv@inf.uc3m.es (A. López-Vargas).

https://doi.org/10.1016/j.heliyon.2023.e12943
Received 12 December 2022; Received in revised form 10 January 2023; Accepted 11 January 2023
Available online 14 January 2023

1.1. Related works on IoT applications for EP monitoring

Smart technology, such as the Internet of Things, has positioned as a powerful tool for tackling EP [8]; IoT plays a key role in real-time monitoring. A bibliometric study on the IoT application on EP alleviation published literature was carried out in alignment with the Preferred Reporting Items for Systematic Reviews and Meta-analysis (PRISMA) 2020 statement [9]. Fig. 2 depicts the findings of the bibliometric analysis of the published literature in the IoT and Energy Poverty area for the last 10 years (from January'12 to December'21). It was identified that more that the 95% of the research works on this field were published in the last 5 years. According to this result, a revision of the state of the art published in the last 5 years on IoT-based systems for EP monitoring was carried out. It was found that the IoT applications focused on EP alleviation could split up mainly into two: energy consumption monitoring systems and thermal comfort monitoring applications.

IoT can be used to improve energy efficiency, increase the share of renewable energy, and reduce the environmental implications of energy use via IoT-based applications focusing on energy consumption monitoring [10]. According to the European Commission report "Benchmarking smart metering deployment in the EU-27 with a focus on electricity" [11], in 2020 Member States committed to rolling out around 200 million of smart meters for electricity and 45 million for gas monitoring by carrying out several initiatives. Fig. 3 shows the electricity smart meter roll-out reached in the EU (connected to telecommunications networks). The roll-out reached by countries such as Finland, Sweden, Italy, and Spain are upper than 80%. The measurement of these smart meters provides key information that can be used for alleviating EP. Fergus, P., and Chalmers, C. [12] presented a new and foundational behavior assessment indicator in 2021, which was aimed to quantify and monitor fuel poverty risks in households using smart meters to measure gas and electricity consumptions. They obtained data every 10 s for all energy consumed within the home at the aggregated level. Each sensor generated up to 30 readings per second and included a) voltage and equipment health monitoring, and b) outage voltage and reactive power management information. In 2020, William Hurst et al. [13] predicted whether an individual household was in an EP situation through the analysis of the gas consumption data captured by a smart meter. In 2020, [14] used gas smart meters data for detecting EP situations improving the wellbeing of occupants in residential properties. They analyzed data from 1033 anonymized residential

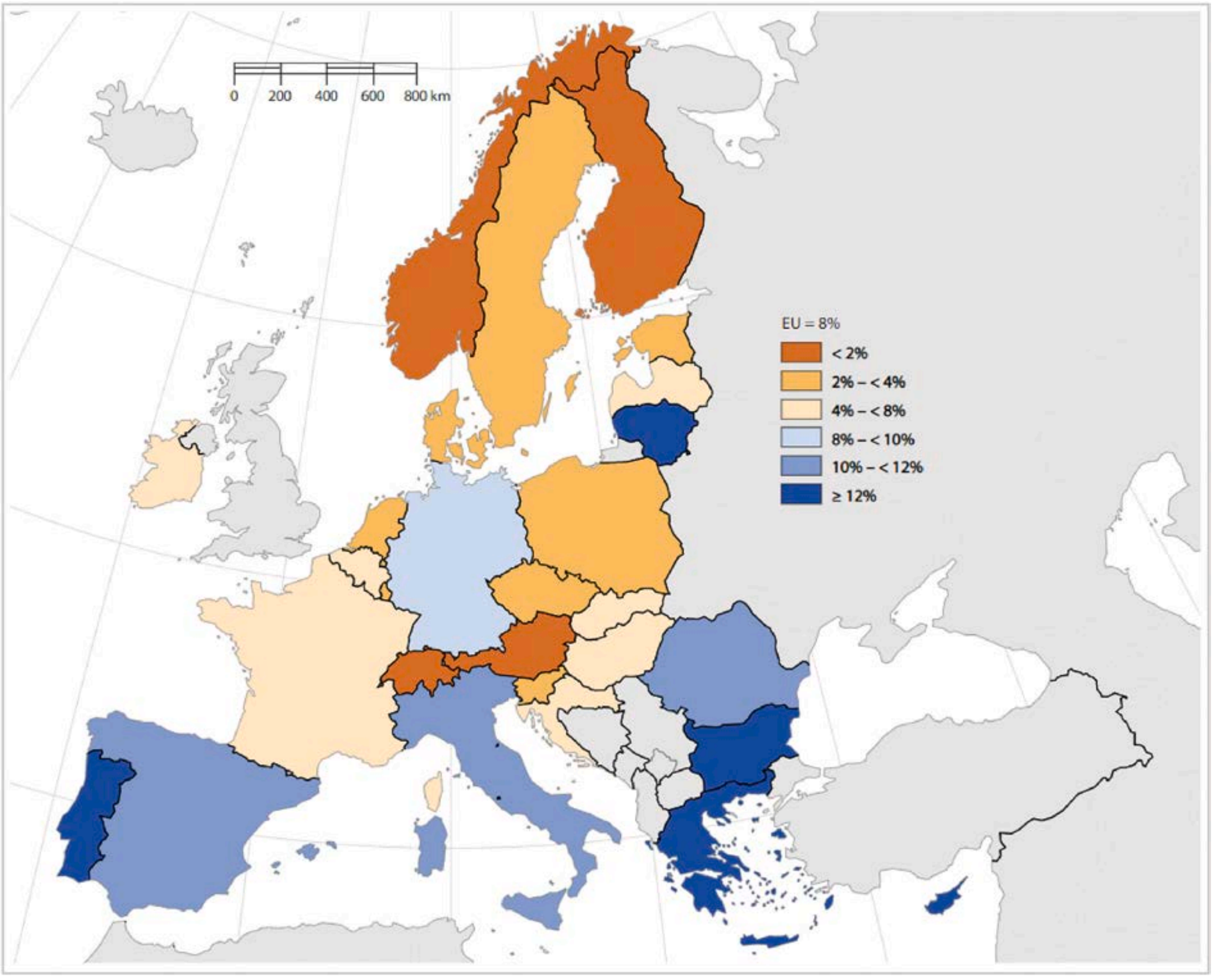

Fig. 1. Energy poverty situation in Europe. 2020 data. Source [5].

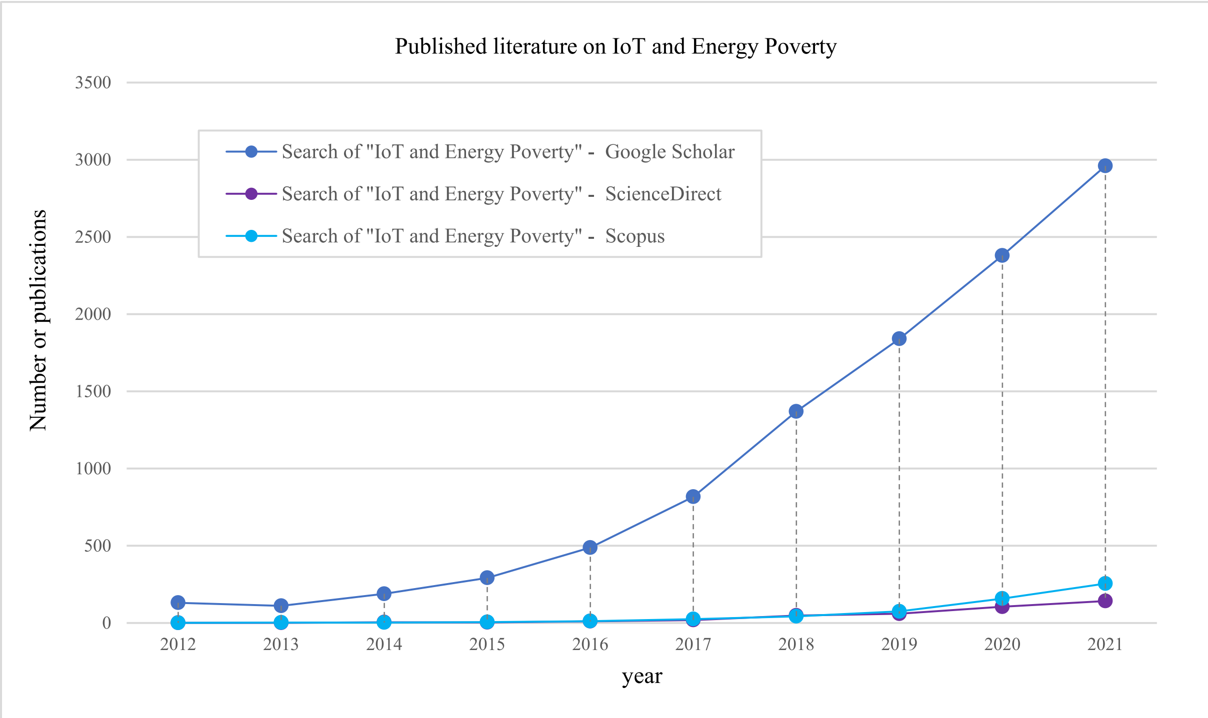

Fig. 2. Number of research works published in the last 10 years related to the '*IoT and Energy Poverty*' area using different scientific databases (Google Scholar, ScienceDirect and Scopus).

premises between 2009 and 2011. Gas meter readings were gathered at a 30-min sample rate.

In recent years, a large number of studies focusing on direct measures of thermal conditions for tackling EP were conducted. However, most of the reviewed research works installed systems without internet connectivity, using local data storage (internal memories) or connecting data to external PCs [16,17]. These systems presented several shortcomings: high maintenance costs (because of an operator for collecting data is required), high hardware costs (PCs), and the impossibility of applying actions in real time. The use of IoT allows reducing maintenance costs and enabling real-time monitoring, so corrective actions to alleviate EP could be applied, and the performance of these actions followed up (without waiting for data a large period of time). However, a limited number of IoT-based applications aimed to monitoring thermal comfort for alleviating EP were found in the published literature. The result of the review carried out was that most of the IoT application for comfort monitoring were designed for other purposes and some parameters that are considered decisive for the EP detection and characterization were not subjected to monitoring. In 2020, A. Pollard et al. [18] studied the use of simple telemetry to reduce the health impacts of EP and living in cold homes. They installed thermometers inside a manufactured bamboo brooch. Thermometers were placed within 34 households of United Kingdom during the 2016–2017 winter. Every 30 min, temperatures were recorded in an automatic way; data were used to draw inference from questionnaire responses, particularly around health and well-being. They concluded that simple telemetry could play a role in the management of chronic health conditions in winter, helping healthcare systems become more sustainable. In 2018, M. Arnesano et al. [19] presented an initiative that included water metering, thermal metering, natural gas metering, comfort (thermal) and indoor air quality monitoring. However, this IoT system used RS485 bus for communicating and it was electricity-network dependent. These two dependencies preclude to install this system in energetic vulnerable homes because of the frequent lack of internet access and the high possibility of power outages. One of the main challenges is detecting Hidden EP (HEP) cases. This identification can be done through massive household monitoring [20], so the low cost of the system is an essential requirement. Several initiatives integrated IoT and Building Information Modeling (BIM) using low-cost systems, carried out the following up of parameters such as temperature, humidity, and air quality [21]. A high number of these initiatives used open-source hardware and open-source software for achieving the low-cost objective.

1.2. Objectives and manuscript structure

The final goal of this work has been to develop an IoT-based system aimed to overcome the shortcomings found in the Energy Poverty detection from the thermal comfort viewpoint. For this purpose, the EP scenario has been studied and relationships between thermal comfort monitoring and EP detection have been identified. The datalogger has been designed, developed, and tested. The main characteristics of the datalogger are: (a) low-cost, by integrating open-source tools, (b) super-low power consumption, with a 2-years of battery autonomy, (c) autonomous operation, independently of a computer or external HW, (d) high precision and (e) reliable. First prototype has been tested under real condition for identifying energy vulnerable households within the EPIU Getafe initiative [22].

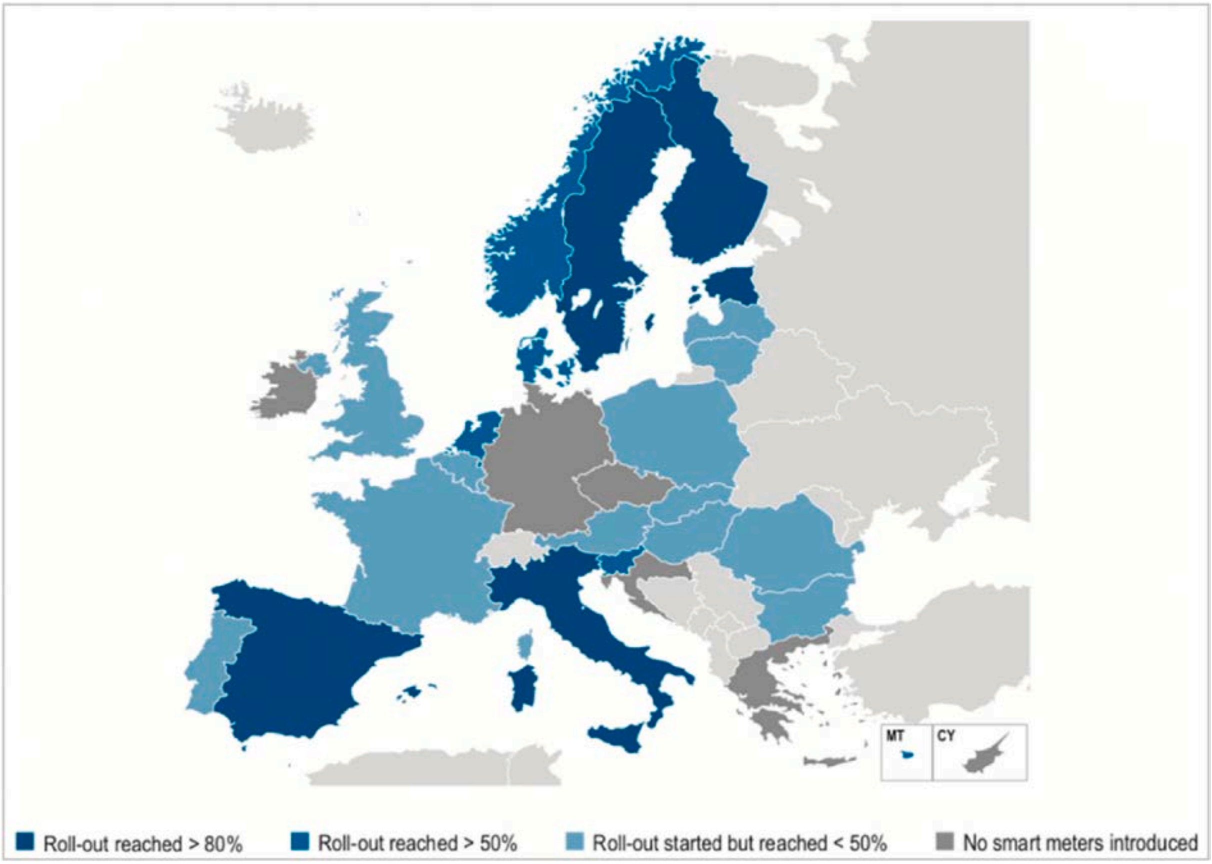

Fig. 3. Electricity smart meter roll-out reached, 2017 data [15].

2. Requirements for the EP monitoring

2.1. EP parameters subjected to monitoring

There is a lack of global guidelines to select the parameters of thermal comfort that should be used for detecting EP. Fig. 4 shows the methodology followed for determining the selection of parameters to measure. First, the study of the existing thermal comfort standards was carried out. It was identified that the most applied thermal comfort standard was the ISO7730 [23], based upon the predicted mean vote (PMV) and predicted percentage of dissatisfied (PPD) thermal comfort indices [24]. Another widely employed standard was the ASHRAE Standard 55 [25] which specifies conditions for acceptable thermal environments, and it is intended for use in design, operation, and commissioning of buildings and other occupied spaces. Studies on EP [26] also applied standards related to other key parameters such as air quality indoor (ANSI/ASHRAE Standard 62.1–2019 "Ventilation for Acceptable Indoor Air Quality" [27] or ergonomics aspects (ISO/TC 159/SC 5 "Ergonomics of the physical environment" [28]. After that, a bibliometric study of the EP works which included the study of comfort parameters was carry out. The aim of this study was to identify the relationship between the comfort parameters established by the standards and the detection of EP. This strategy allowed to limit the number of variables to be measured and therefore the number of sensors, increasing the useful life of the battery and reducing the costs of the systems (both, construction and maintenance costs).

According to the results obtained in Section 1.1., the number of articles studied was limited by published date: the study was focused on research works published in the last 5 years. The influence of each of the parameters described in the thermal comfort standards and their impact in the identification of EP was studied. A thorough database search of Google Scholar was conducted to

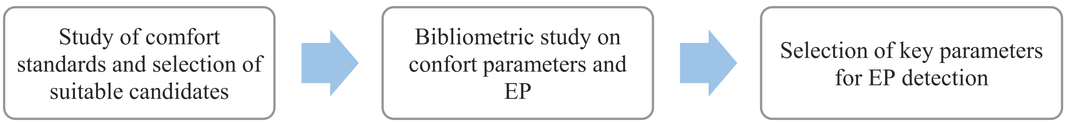

Fig. 4. Methodology employed to design the thermal monitoring system for detecting EP.

retrieve and analyze the most cited articles in each topic. The topics were generated by combining thermal parameters jointly with the EP key "fuel poverty". Fig. 5 shows the result of the bibliometric study carried out. According to the findings of this bibliometric study, the most used thermal-related parameters (indoor) for the detection of energy poverty are 3: air relative humidity (24.07%), air quality (29.73%) and air temperature (30.08%).

The reviewed studies used the occupation of the dwellings to establish the comfort conditions. This necessitates the inclusion, in addition to the previously mentioned parameters, of a sensor that provides information on the occupants of the house. Among the methods to measure occupancy, the measurement of light allows following up ergonomic comfort as well. As a result, the most important metrics for monitoring IoT were revealed to be air relative humidity, air quality, air temperature, and light.

2.2. Ranges of the EP measurements

In this Section, the values of the thermal comfort sensors were established; these values determined the sensors selections (thresholds, resolutions, etc.). The relationship between air temperature indoor level and health has been studied profusely from different perspectives. When comparing healthy levels with comfort levels, several differences were found; generally, the values harmful to health are more extreme than the values in which people have a comfortable feeling at home. The standards recommend ranges around 23–26 °C in summer and 21–23 °C in winter [23,25]. The World Health Organization's (WHO) recommends indoor air temperature ranges of 18–24 °C (according to the specific function of the room) for non-vulnerable population, and 20-24 °C in case of vulnerable households [29]. The ranges of the parameters also vary depending on the season of the year. In 2014, the Public Health England established the adequate minimum temperature threshold for homes in winter [30]: at least 18 °C in winter poses minimal risk to the health. [31] limited the upper temperature indoor threshold to 26 °C in summer and showed evidence of the impact of high temperatures in human health. Sometimes, the recommended indoor temperature ranges are outside the usual limits: i.e., for reducing sudden infant death syndrome (SIDS), the advice is that rooms in which infants sleep should be heated to between 16 and 20 °C [32]. Standards recommend relative humidity ranges of 30–60% [23,25]. Inadequate levels of relative humidity cause respiratory infections and allergies [33]. According to Ref. [33], relative humidity levels between 40% and 70% reduce the survival and infectivity of bacteria and viruses. CO_2 level is another key parameter to measure in energy vulnerable households: This gas is produced by metabolic processes (i.e., respirations) and fossil fuels combustions. Indoor levels of CO_2 are usually higher than in the open (300–400 ppm) mainly due to the CO_2 exhaled by households' occupants. According to standards, the CO_2 level should not exceed 2500 ppm, while 1000 ppm is the recommended value [23,25]. High levels of CO_2 cause acidification of the blood with compensatory increase in rate and depth of breathing [34]. Light measurements provide key information on occupation as well as adequation lighting (intimately linked to extreme EP cases). Safety visual performance requires adequate lighting levels. Light also plays an important role in regulating human physiological functions. Poor illumination has negatively consequences in health, linked to falls and depression. Around 200 lux is the level recommended for general household activities [35].

2.3. Sampling time fitting

The duration of the measurement campaign of thermal comfort in the context of EP should be at least one year aimed to obtain data

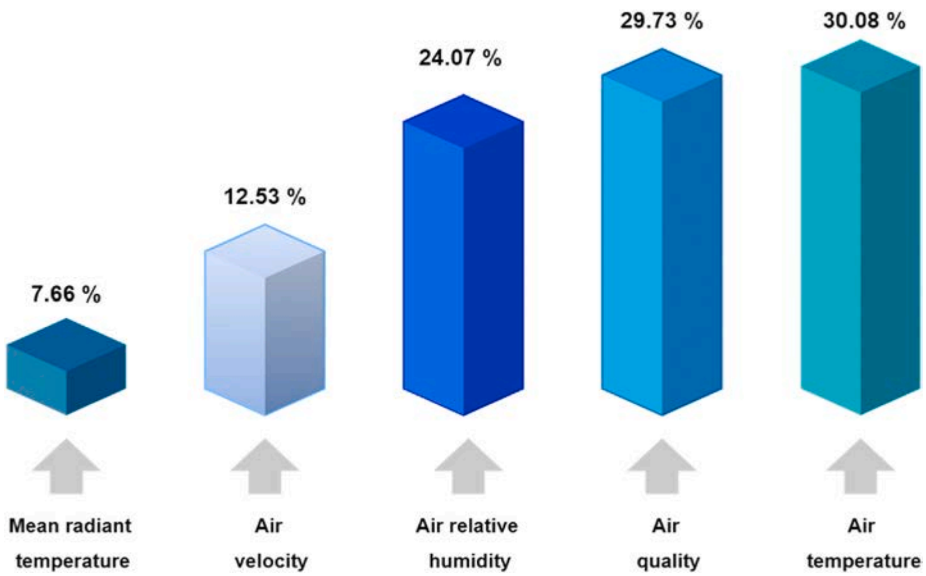

Fig. 5. Results of the bibliometric study using "Parameter" and "Fuel poverty" key. Google Scholar database was used and research works published from 2018 onwards were reviewed.

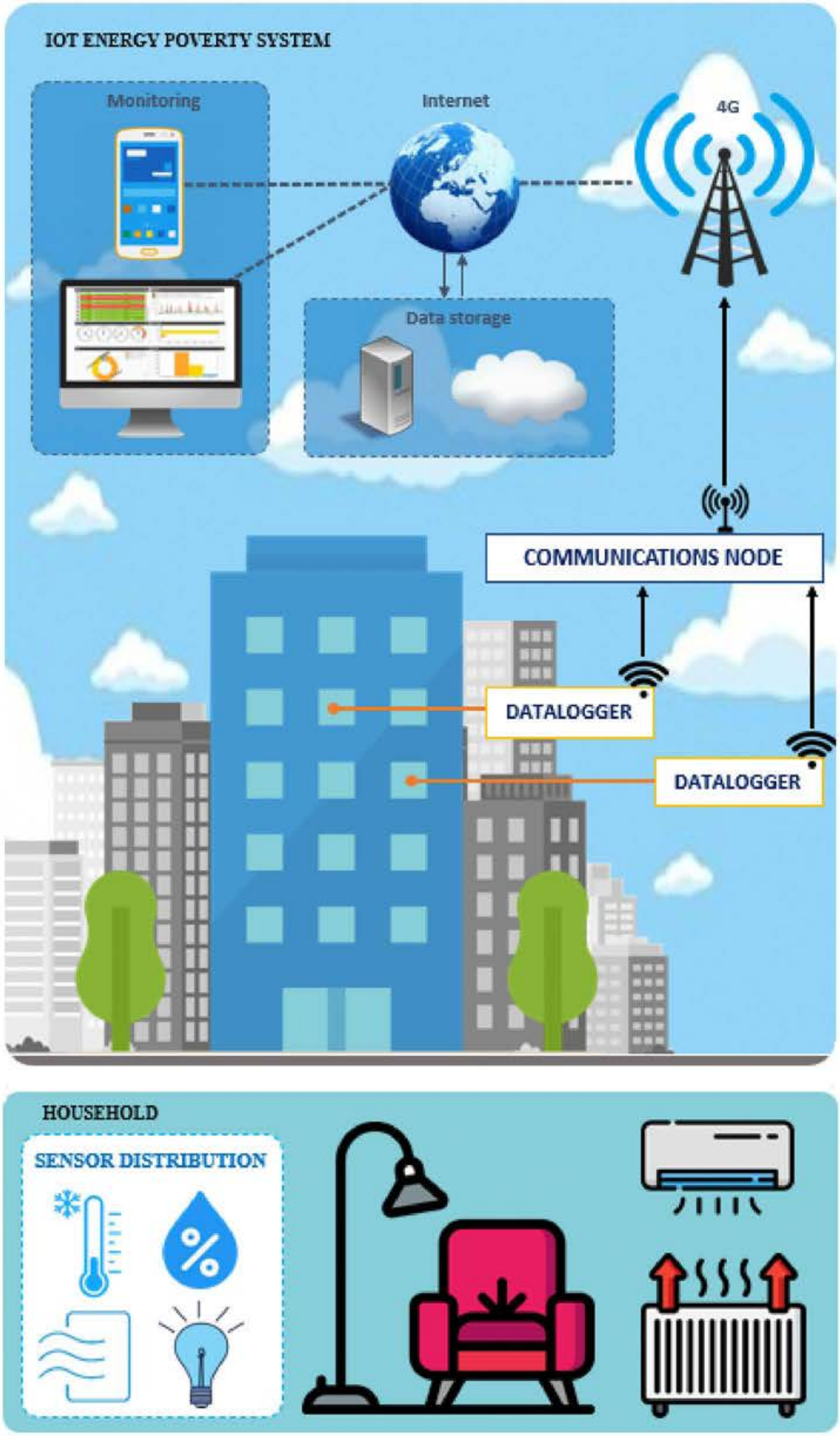

Fig. 6. Diagram of the final smart datalogger for following up thermal comfort in energy vulnerable households.

during the different seasons of the year. For this reason, the selection of the sampling time is a critical aspect of this application as it has direct consequences on the cost of the system: the higher the frequency of measurements, the shorter the long-life of the battery. The shortening of the long-life of the battery has a very negative effect on the final cost of the system, mainly due to the increase in maintenance costs. The objective was to adjust the sampling time to the minimum that did not affect the quality of the measurements. In 2020, William A. Gough [36] studied the range of sampling from hourly to twice daily and accurately determined the error introduced by different sampling times. They focused on less frequently sampling times than hourly using as a guide average and extrema temperatures. 24 h sampling remained the gold standard for determining daily mean temperature and the introduced error was around 0.1 °C. They also stated that bi-and tri-hourly sampling introduced an error of less than 0.2 °C whereas two even samples per day had an error near 1 °C.

2.4. Location of the datalogger

The measurement locations are established by the ASHRAE 55 [25] standard. According to the standard, the recommended location for measuring thermal comfort parameters is in frequented zones of the building at areas where the residents are known to or expected to spend their time. Depending on the role of the room, these sections might be workstations or sitting areas. Measurements should be collected at a representative sample of occupant locations scattered across the occupied zone in inhabited rooms. In vacant rooms, the evaluator should make a reasonable assessment of the most likely future occupant positions and take relevant measurements. If an estimation of the occupancy distribution is not possible, the following measurement locations must be used: a) in the room's or zone's center and b) in each of the room's walls is 1.0 m inward from the center. The measuring position for external walls with windows is 1.0 m inward from the center of the biggest window. In either instance, measurements should be done in areas where the most extreme values of the thermal parameters are predicted or observed. Near windows, diffuser outlets, corners, and entrances are all good instances. Measurements should be taken far enough away from the occupied zone's boundaries and any surfaces to allow for adequate circulation around measurement sensors in the places mentioned below. In any inhabited room or HVAC-controlled zone, a measure of absolute humidity (such as humidity ratio) should be obtained at just one site inside the occupied zone, provided that there is no reason to predict considerable humidity changes within that area. Otherwise, absolute humidity should be measured at all the above-mentioned places.

2.5. Internet connectivity

According to Ref. [37], by 2021, the share of EU households with internet access had risen to 92%, and as of the beginning of 2021, almost nine out of ten (89%) individuals in the EU (aged 16–74 years) used the internet. The internet access in rural regions (89%) is

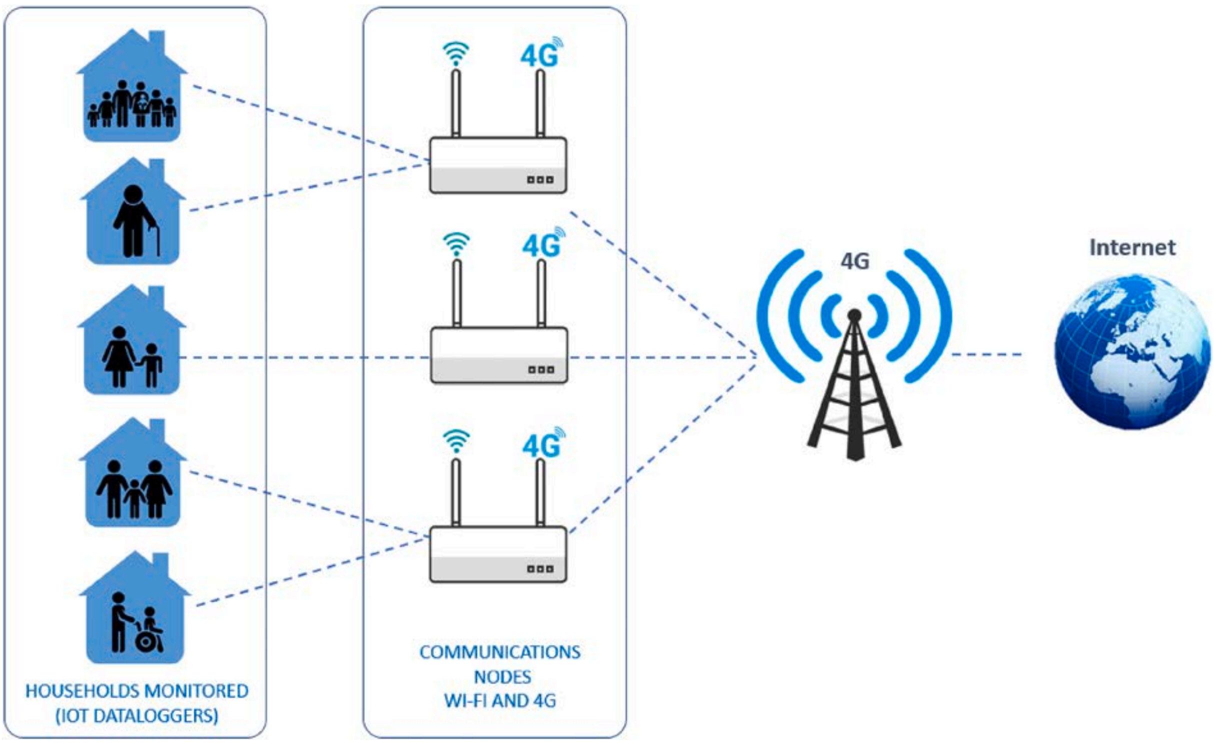

Fig. 7. General diagram of the telecommunications environment.

less than in urban areas (92%), being particularly strong this division in Bulgaria, Portugal, Greece, Croatia, and Romania. Recently, several studies on Internet Poverty were carried out [38]. In 2022, S. Wang et al. [39] studied the impact of EP on the internet perception. They found that energy poverty significantly reduces Internet use not only directly but also indirectly through the mediating effects of Internet perception. According to these results, the probability of lacking internet access is greater in households that suffer from EP. In addition, in case of extreme EP such as the Cañada Real with areas that does not have access to electricity, internet networks are not available [40]. Summarizing, due to the peculiarities of monitoring EP, the selection of the communication system for transmitting data is conditioned and the use of communications systems with no internet infrastructure dependency provides great advantages.

3. Design of the IoT-based system for EP monitoring

3.1. Description of the system

The general diagram of the new EP monitoring system is depicted in Fig. 6. The basic distribution for monitoring EP households as well as the communications systems are shown. The smart datalogger follows up selected EP related parameters. Dataloggers send the measured information to the communication node via Wi-Fi. The communication node send data via 4G, and collected information is stored in a cloud server (a dedicated server could be also compatible). If the energy vulnerable households subjected to monitoring are close enough, several dataloggers could be connected to a single communication node. The ability to monitor energy-vulnerable households from any device or computer is enabled by the internet connection.

3.2. Selection of the communication technology

As stated in Section 2.5., the selection of the type of telecommunications is determined by the scope of application. After studying all the available technologies and network typologies, a combination of wireless technologies was selected as the most suitable option. Fig. 7 shows the communication network designed for monitoring EP. This network is composed by two types of nodes: the communication nodes (a mobile communication node acting as Gateway) and the households' nodes (datalogger itself). Dataloggers use IEEE 802.11 protocol (Wi-Fi) for communications. The communication node creates a Wi-Fi-based local network for communicating with dataloggers. The GSMA Report entitled "The State of Mobile Internet Connectivity Report 2021" [41] stated that around the 94% of the world's population now have access to a broadband network. The high coverage was the reason for selecting mobile communications for sending data; this node allows the vulnerable households to be provided with connectivity regardless of the existing infrastructure. This system does not require prior installation. The dataloggers includes sensors and send data to the communication node using the Wi-Fi. This topology allows to connect several households to the same communication node (if distance is close enough). In addition, if Wi-Fi is available in the household subjected to monitoring, the communication node could be removed (without changing the design) and costs are reduced.

3.3. Hardware

The most suitable HW was selected based on the use of open-source technologies, which allowed the final system to achieve the low-cost goal. The specific communication protocol of the dataloggers (Wi-Fi, see Section 3.2.) limits the search for microcontrollers. Among the many systems based on open-source hardware that are now available on the market, the ESP32 NodeMCU-based board stands out from the rest because to its communications features, low-cost, and developer community (including academic) [42]. NodeMCU is an open source IoT Platform and ESP32 is a powerful SoC (System on Chip) microcontroller with inbuilt Wi-Fi 802.11 b/g/n, dual mode Bluetooth, and a range of peripherals. The board employs a Tensilica Xtensa LX6 microprocessor with a clock rate of 240 MHz. It includes 36 GPIO pins, 16 PWM channels, and 4 MB of flash memory. The selected board supports SPI, I2S, I2C, CAN, UART, Ethernet MAC, and IR. The benefits of using this environment are its simple configuration and the great community support [42]. The software is free to download, and the hardware reference designs are available under an open-source license, allowing users to customize designs to their specific needs. A global development community works around this open-source platform, and help is accessible on various websites, including examples and libraries. The resolution, on the other hand, is one of the board's major flaws. The board features 16 analog inputs and an ADC with a maximum resolution of 12-bits.

Various HW improvements were carried out. Although the design includes digital sensors, the on-board ADC is used to monitor the state of battery charge. Testing determined that the ADC on the board was not accurate enough and gave inconsistent data. To solve this issue, an external ADC has been integrated. The ADC selected was MCP3202 from Microchip™. The MCP3202 is a successive approximation 12-bit converter with on-board sample and hold circuitry. The MCP3202 is programmable to provide a single pseudo-differential input pair or dual single-ended inputs. Differential Nonlinearity (DNL) is specified at ± 1 LSB, and Integral Nonlinearity (INL) is offered in ± 1 LSB [43]. Other HW improvements were developed to reduce power consumption on the board. One of the main requirements of the system is that it works independently of being plugged in, for that an external battery is integrated. The selected battery was the ER26500 $Li–SOCl_2$ from EEMB [44], a C-battery with nominal voltage of 3.6 V and nominal capacity of 9000 mAh. The operating temperature range is -55–85 °C and the discharge cut-off voltage is 2.0 V. In reduced power mode, the board consumed 9 mA. After different tests, it was found that most of the board's consumption came from the programmer (only required when loading the SW). The HW improvement consisted of eliminating the related programmer circuit during the measurement period, thus achieving a reduced power consumption of 1 mAh.

3.4. Selection of the EP sensors

EP parameters selected for monitoring were relative air humidity, air temperature, air quality and occupancy (see Section 2). Table 1 shows a brief comparison of the most widely used low-cost temperature sensors. After studying the different options, the BME280 sensor from Bosch™ was selected because with a single sensor 3 parameters can be measured, the range of measurements covers the requirements (see Section 2.2.) and the error is very small. The use of the BME280 allows to obtain pressure, so it can be used as altimeter; this information could be useful for determining the influence of the floor and the thermal comfort. In addition, costs are reduced because of a) the number of sensors is lowered (1 sensor is purchased instead of 3) and b) the consumption of 1 sensor is lower than three it extends the useful life of the battery, which translates into a reduction in the costs of purchasing batteries and the maintenance costs derived from replacement. The reduction of sensors to the minimum number necessary also optimizes the system design by reducing the number of pins needed.

[48] assessed the long-term performance of a datalogger under difficult environmental conditions, and degradation in sensors was identified as the most pernicious damage. The temperature-humidity sensors failed. The sensor successfully recorded temperature, but the humidity value was incorrect: even on bright days, the relative humidity was 100%. The temperature and humidity measurements are vital data for evaluating EP, so it was decided to integrate two sensors measuring the same parameters (temperature and relative humidity) in a redundant way. The redundant selected sensor was DHT22 from Aosong™. The installation of a redundant sensor avoids the loss of information and reduces the final costs because of the cost of a second sensor is less than the maintenance cost of replacing the sensor if broke. In addition, [49] found several difficulties when trying to have access to the individuals; reducing visits to a minimum is another of the objectives accomplished with the integration of redundant sensors. The air quality sensor selected was CM1106SL-NS from Cubic™ [50]. The main problem observed when measuring CO2 using low-cost sensors (such as MQs family sensors) was the high consumption. The CM1106SL-NS sensor is a low-cost and low-power consumption; it is a high-performance non-dispersive infrared (NDIR) battery-powered sensor that can follow up CO2 concentrations in indoor air using NDIR technology. Its measurement range is 0–5000 ppm and the accuracy is ±50 ppm+(3–5) % of reading. Two communications modes are available: UART and I2C. UART was the mode implemented for this application. The light sensor selected was the BH1750 sensor from ROHM Semiconductors™, a digital ambient light sensor IC for I2C bus interface [51]. This sensor presents a wide and high-resolution range: 1–65535 lx.

3.5. Software description

The algorithm has been coded using C/C++ based subset language, using the Arduino™ IDE (open-source software). Fig. 8 summarizes the flow diagram including the main processes carried out by the microcontroller. First, the internet connection is created at the start; this process is repeated every time the routine is started, or the reset button is hit. Hourly sampling allows to extent the long-life of the battery with a minimum error (see Section 2), so parameters are measured every 60 min, and after that, data transmission and storage activities are carried out. Throughout the development of the system, the reduction of consumption has been essential. As was the case with HW measurements, SW strategies have been developed to suspend the microcontroller at minimum consumption. After transmitting data, the power reduction mode starts by enabling a deep sleep mode. The establishment of the internet connection, the connection with the server and the sleeping period are the processes that could have a greater impact on the long-life of the battery.

Different tests have been carried out to adjust these times. 25 cycles of measurement were recorded and studied for fitting the time for waiting reconnection and sleeping. Table 2 summarizes the results including the different times (minimum, average and maximum) for each process. After studying, 10 s was the maximum time selected for establishing the internet connection. Each cycle, the microcontroller works less than 10 s (in worst case) consuming around 100 mAh; 99.72% of the time the microcontroller is sleeping, and the consumption is extremely low (less than 1 mAh). According to the consumptions worked out, the expected long-life of the battery is 197 days (in average).

Table 1
Comparison between low-cost temperature-humidity sensors available in the market.

Characteristic	Temperature-humidity sensor model		
	BME280 [45]	DHT11 [46]	DHT22 [47]
Measures	Temperature, humidity, and pressure	Temperature and humidity	Temperature and humidity
Communication protocol	I2C, SPI	1-wire	1-wire
Supply voltage [VDC]	1.7–3.6	3.3–5.5	3.3–6
Operating range	−40 to +85 °C 0–100% rel. humidity 300-1100 hPa	0 to +50 °C 0–100% rel. humidity	−40 to +80 °C 0–100% rel. humidity,
Consumption	3.6 μA (measurement) 0.1 μA (sleep mode)	0.3 mA (measurement) 60 μA (standby)	1.5 mA (measurement) 50 μA (standby)
Accuracy **(at 25°C)**	±3% RH ±0.5 °C <1.7 hPa	±5% RH ±2 °C	±2% RH ±0.5 °C
Price [€]	8,67	6.04	6,36

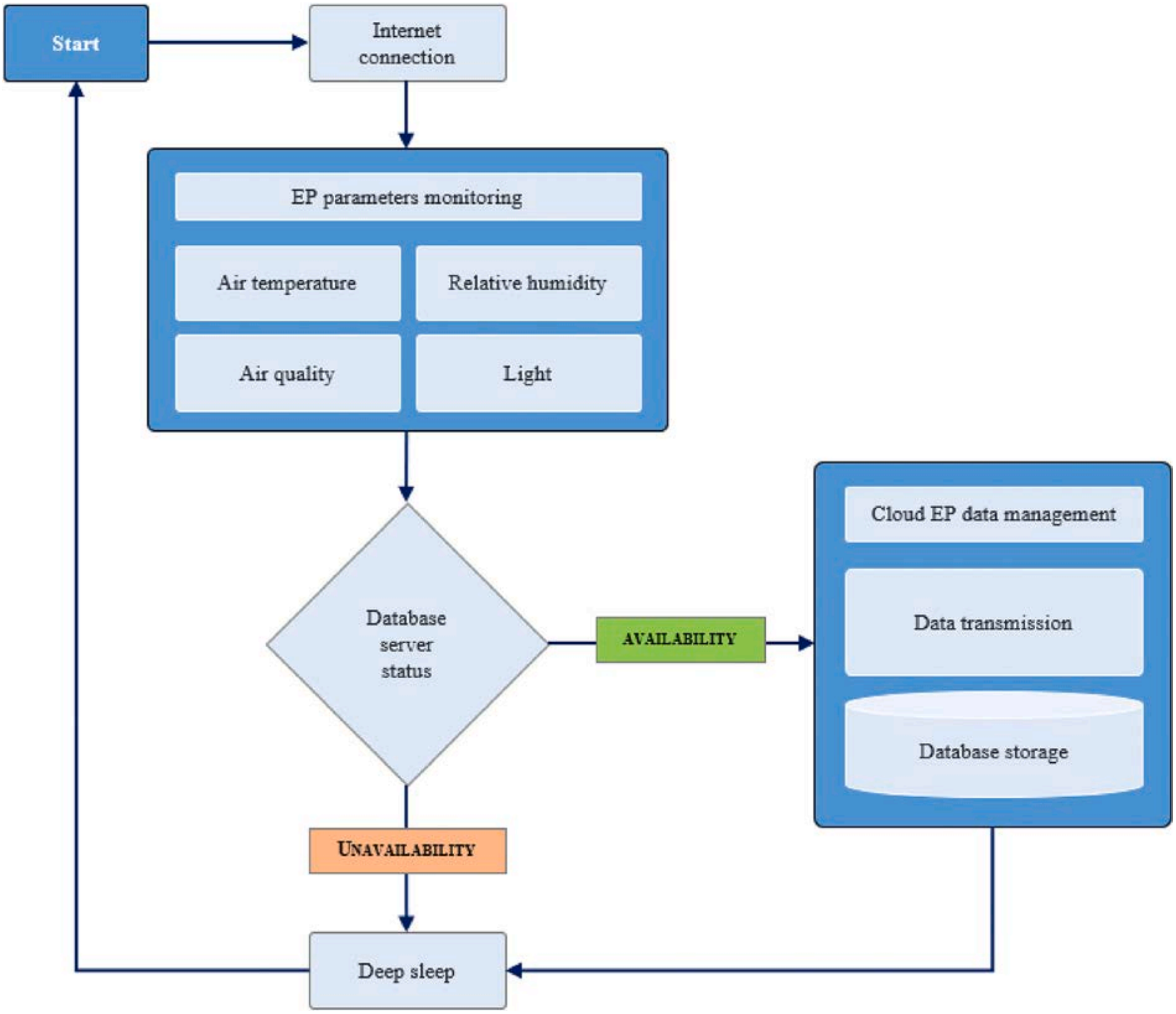

Fig. 8. Flow diagram of the EP monitoring system.

A HTTPS petition establishes the connection between the microcontroller and the server. The data transmitting procedure begins when the datalogger and server have established a connection. InfluxDB [52] was the cloud platform selected for storing data. Influx DB is ranked number one in the list" DB-Engines Ranking ranks database management systems according to their popularity" as of May'22 [53]. InfluxDB is an open-source schemeless time series database created by InfluxData with optional closed-source components. It's developed in the Go programming language, and it has a query language that's like SQL. Every InfluxDB database has a time column that maintains discrete timestamps that relate to specific data. Each field is composed by a field key and a field value. 4 EP parameters are measured (from 4 sensors). 11 fields are transmitted every cycle: air temperature (TH22) and air relative humidity (HH22) from the DHT22 sensor; gas concentration (CO2); air temperature (TBME), air relative humidity (HBME), altitude (ABME) and pressure (PBME) from the BME280 sensor; light (LBH) from the BH1750 sensor; the board current (ADC0) and the battery voltage (ADC1); the number of cycles without reboots (bootCount).

Table 2
Results of 25-cycle periods for studying the impact of the internet connection time in the long-life of the battery.

Measurement	Time of entire cycle [ms]	Time for Wi-Fi connection [ms]
Minimum	5271	3190
Average	5791.12	3530.76
Maximum	8373	6178

4. Experimental setup

Getafe is a southern city of Madrid, Spain, located at 622 m.a.s.l., with a maximum average temperature of 32 °C in summer and lowest average temperature of approximately 1.5 °C in winter. The yearly average temperature is around 15 °C [54]. EP affects up to 30% of individuals in Getafe, and there are 156 receivers of the Integration Minimum Income for every 10,000 residents [22]. The situation is much worse in Getafe's "Las Margaritas" and "La Alhóndiga" areas (both designated as Urban Regeneration Areas by the Spanish Government [55]). According to the Getafe Municipality Report developed in 2018 [56], the area Las Margaritas – La Alhóndiga comprises a total of 207 buildings and 4814 homes in two areas: about half of these homes lack heating systems, and approximately 235 households need aid to pay for basic supplies and rent [22]. The areas of 'Las Margaritas' and 'La Alhóndiga' were built in the second half of the 20th century, before the creation of the of NBE-CT 79 [57] standard on thermal conditions in buildings (the first modern standard requiring thermal insulation in Spain). Therefore, a large part of the households does not meet the requirement established in the thermal insulation legislation. Fig. 9.a shows the vulnerable area of Getafe "La Alhóndiga"; Fig. 9.b depicts one of the neighborhood's typical structures.

The UIA "EPIU Getafe Hogares Saludables" [58] proposes to identify and eliminate EP in Getafe, (Spain), by utilizing new technologies such as IoT and AI. The first pilot of the datalogger was installed under the EPIU Getafe project in one of the households participating in the initiative. Some of the households have been selected because they meet some of the typical indicators of suffering energy poverty, others do not. This last category will serve as the basis for identifying cases of hidden energy poverty through monitoring.

Fig. 10 shows the aerial view of the entire Urban Regeneration Area "La Alhóndiga", including the location of the first protype installed. The building is composed by 5 floors, the household subjected to monitoring is located on the first floor of the building, with East orientation. The datalogger was installed in the main room, at 1.5 m high and far away from any heat/cold sources.

5. Experimental results

The final prototype of the new low-cost datalogger placed in Getafe is shown in Fig. 11a. Fig. 11b shows the encapsuled datalogger. The first pilot of the datalogger was installed in 16th june'22. Since that day, the developed system has carried out all measurement cycles without internal errors (counted by an internal counter developed by SW for measuring fails in the measurement process and rebooting).

One entire month was used for the pilot evaluation. This period includes two heat waves: a heat wave in mid-June'22 that lasted a week and was said to be the earliest recorded in almost 40 years and the second wave in mid-July'22 with temperatures surpassing 40 °C. The findings of the testing period revealed that the new EP datalogger successfully monitored with a 0.7564% of unavailability, so it was confirmed that the datalogger is highly reliable. These fails were due to connection failure or server access failure. For evaluating the quality of the measurements, the new EP datalogger was compared to a commercial monitoring system that acted as a pattern. This pattern commercial monitoring system was an Imbuilding™ datalogger. Table 3 includes technical characteristics of the pattern datalogger. Every 15 min, this commercial datalogger measured and recorded the same parameters as the EP datalogger.

5.1. EP measurements: comparison with commercial datalogger

Fig. 12 shows an example of the daily variations of the air temperature measured by three different sensors: 2 integrated in the developed datalogger and the third one of the commercial datalogger. The 18 June'22 Madrid melts under the earliest heat wave in over 40 years due to a cloud of hot air from North Africa [59]. Both dataloggers were located in the same place. The temperature measured by the datalogger using low-cost sensors under real conditions shown in Fig. 12 demonstrate the correct functioning of the EP datalogger. Related to the DHT sensor, the daily mean error of the air temperature measurements was −0.099 °C with a variance of 0.285 °C compared to the commercial datalogger. In the case of the BME sensor, the daily mean error was −0.328 °C with a variance of

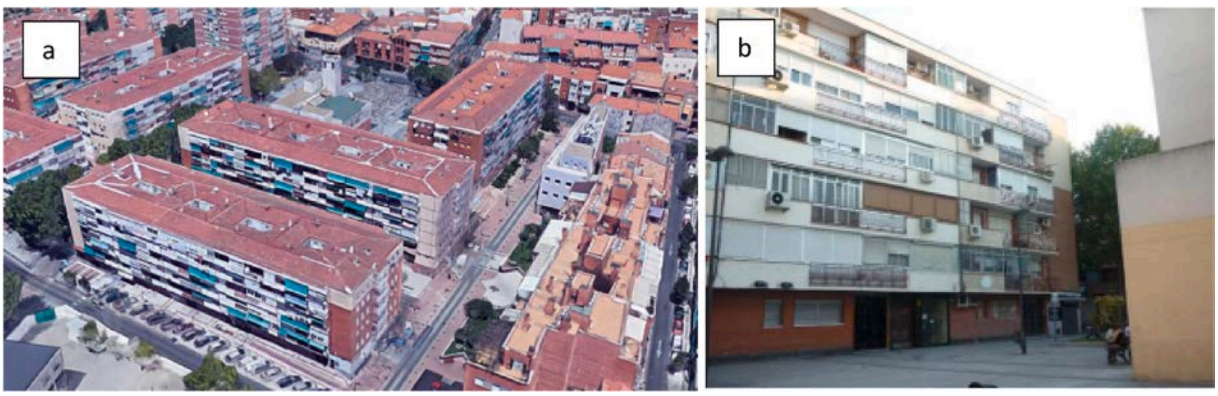

Fig. 9. Aerial view of the vulnerable area of Getafe "La Alhóndiga" (a) and typical buildings of the neighborhood (b). Source [56].

Fig. 10. Urban Regeneration Area "La Alhóndiga" with the location of the first prototype installed [56].

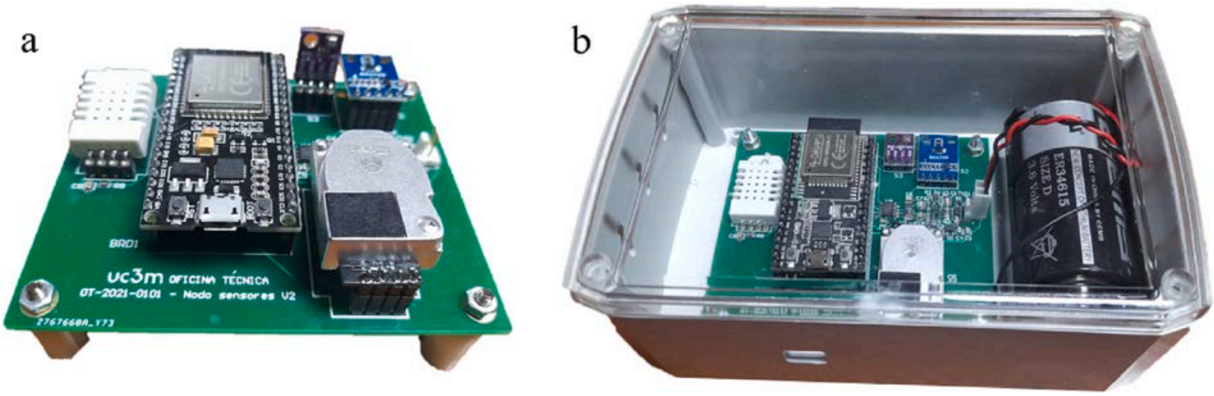

Fig. 11. Final design of the EP datalogger final pilot (a) and the integration of the board in the protector capsuled (b).

Table 3
Pattern datalogger characteristics.

Parameter	Accuracy
Air temperature	0.2 @0–65 °C
Air relative humidity	2% @ 10–90%
CO_2 level	30 ppm + 3% reading @ 400–50000 ppm

0.0717 °C.

In the same way, the air relative humidity was measured using 2 sensors of the EP datalogger and another one belonging to the commercial datalogger. Fig. 13 shows the daily collected data. Related to the DHT sensor, the daily mean error of the relative humidity measurements was −0.454% relative humidity with a variance of 3.951% (compared to the commercial datalogger). In the case of the BME sensor, the daily mean error was −0.093% with a variance of 0.500% relative humidity.

Fig. 14 shows the performance of the CO_2 sensor calibration. Uncalibrated sensors showed a high dispersion in medium and high values of CO_2 concentrations because of the dependence between error and measured value. After calibrating, the results showed that the dataloggers measure close values in all ranges (according to the bias line).

Fig. 15 shows the daily variations of CO_2 concentration measured by the pilot installed in a household of Getafe. The indoor air quality was measured with the commercial datalogger and the EP datalogger. The daily mean error of the relative humidity measurements was 25.89 ppm.

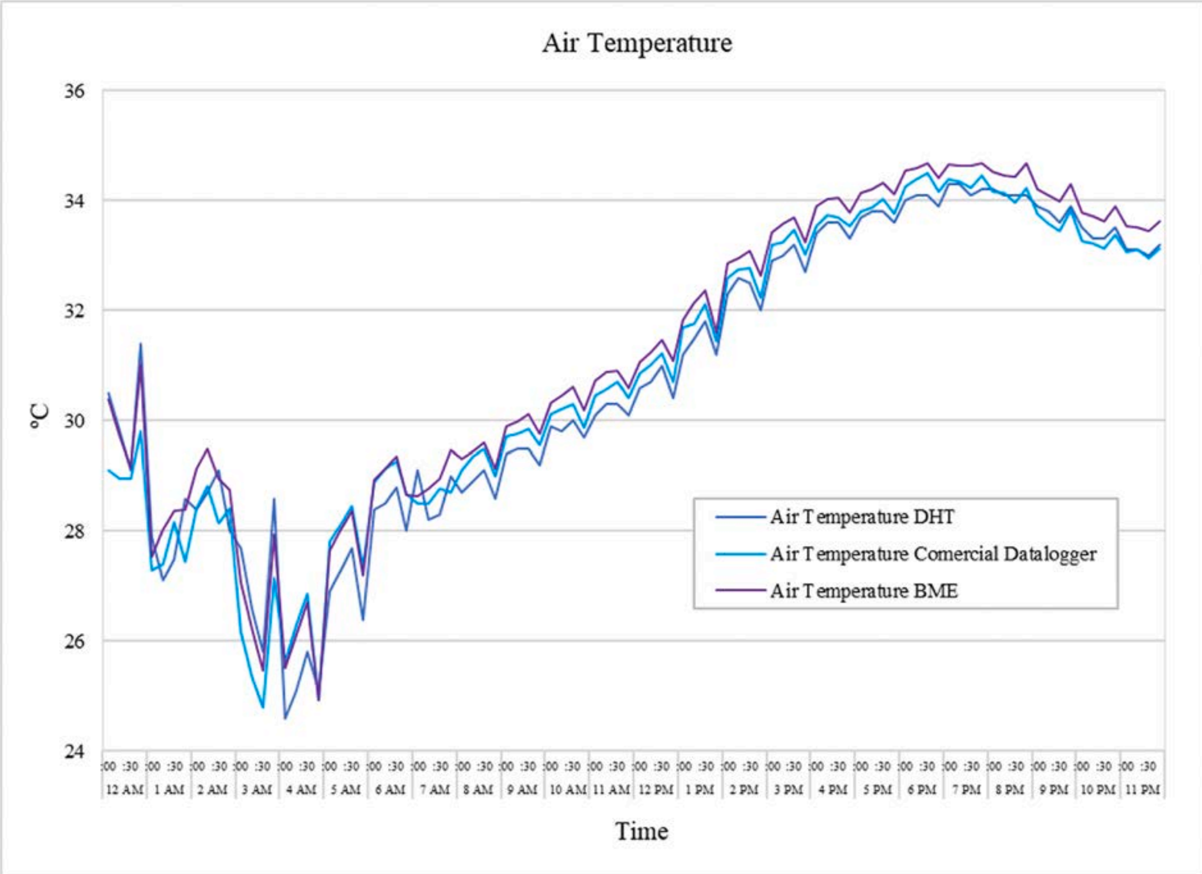

Fig. 12. Air temperatures measured in Getafe (18th June 2022) using the EP dataloggers (BME and DHT temperatures) and the commercial datalogger.

5.2. Visualization of the measurements

As the main novelty of this work, the remote visualization of the data in real time via web stands out, due to the incorporation of connectivity to the system. Fig. 16 shows the visualization of temperature data measured and sent to the cloud from 17/06/2022 to 22/06/2022 in Getafe. The open cloud platform selected, InfluxDB™, allows to monitor selected parameters.

6. Estimation of the initial prototype's costs

The final purpose of this project was to create a low-cost, accurate, and self-contained IoT-based datalogger prototype that leverages a mobile communication transmission technology for monitoring EP. The monitoring system's budget is shown in Table 4.

The new prototype's total cost, including sensing and connectivity, was around 91 euros. This cost is lower than that of commercial systems with similar characteristics [60]. When mass manufactured and brought into the market, total costs might be significantly lowered. The budget for the communication node is around 45 euros. The budget for the total system (including datalogger and communication node) was 136 euros. Due to the usage of a 4G SIM card, this monitoring system includes a maintenance fee (around 35 € per year).

7. Conclusions

When detecting EP, there are two main issues that could be addressed by installing the datalogger developed in this work: a) the lack of aggregated data for identifying EP and b) the lack of monitoring of thermal comfort in energy poor households. The novel datalogger for identifying EP via thermal comfort monitoring in real-time and remote way has been designed, built, and tested incorporating wireless technology in it, along with IoT. The installation of the developed datalogger allows revealing HEP situations, cases that are very difficult to detect by other mechanisms that do not include direct measurements.

The developed system has been designed ad-hoc to measure air temperature, air relative humidity, air quality and lighting. The IoT application developed do not required access to electric network, with a 2 years of power independence. 1 h sampling rate has been set

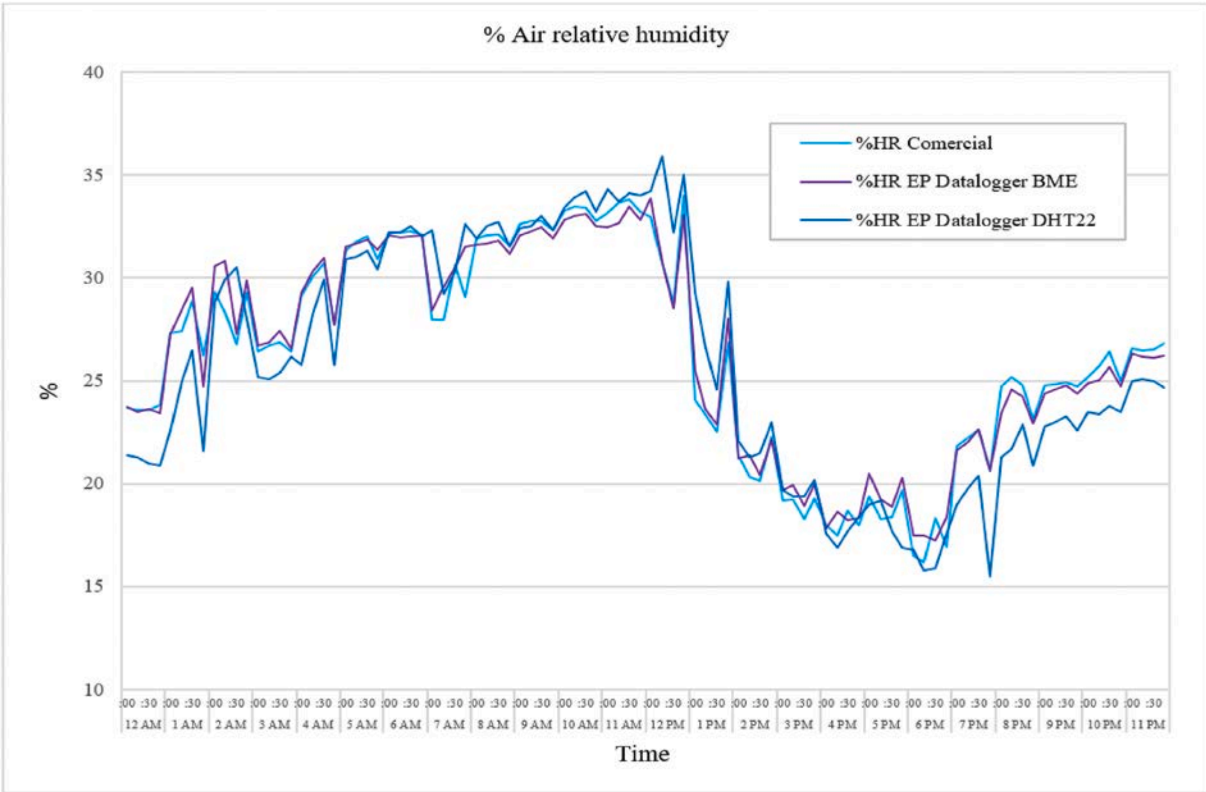

Fig. 13. Relative humidity measured in Getafe (18th June 2022) using the EP dataloggers (BME and DHT humidity levels) and the commercial datalogger.

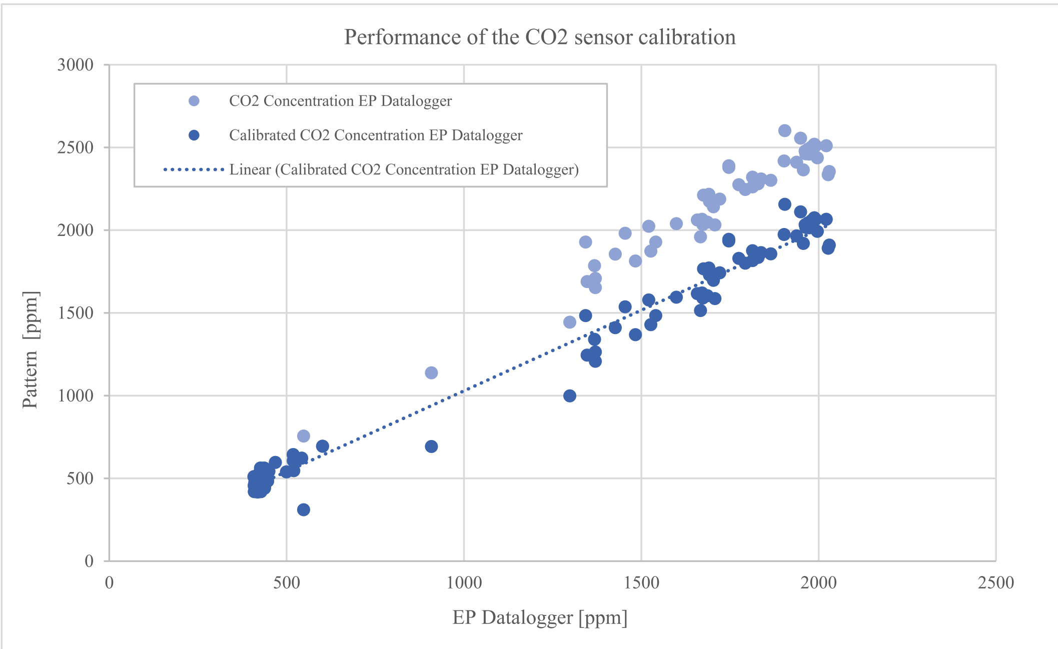

Fig. 14. Dispersion diagram of the performance of the CO_2 sensor calibration.

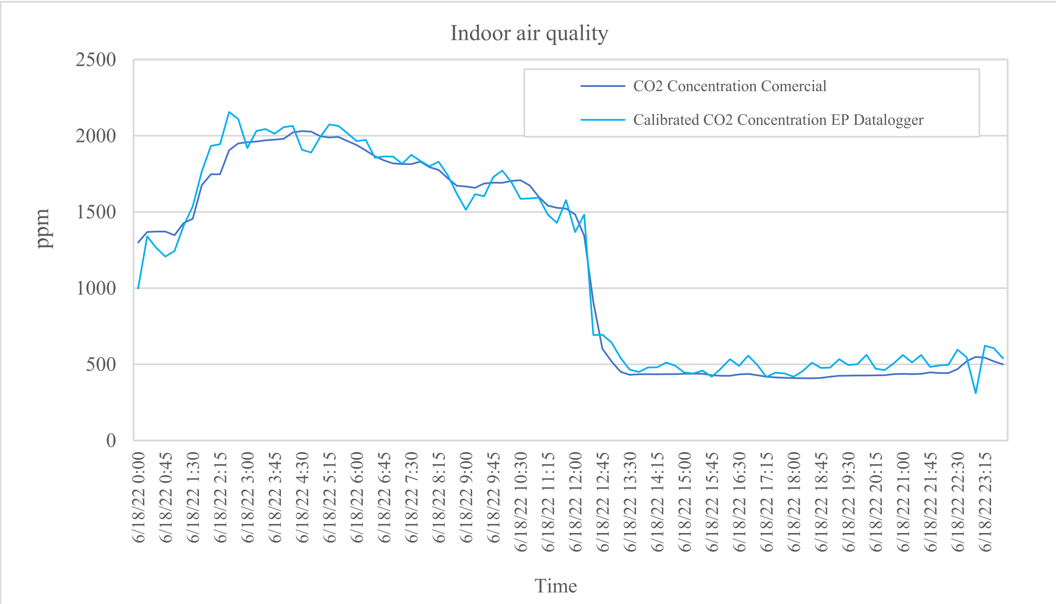

Fig. 15. CO_2 level measured in a household of Getafe (18th June 2022) using the EP dataloggers (BME and DHT humidity levels) and the commercial datalogger.

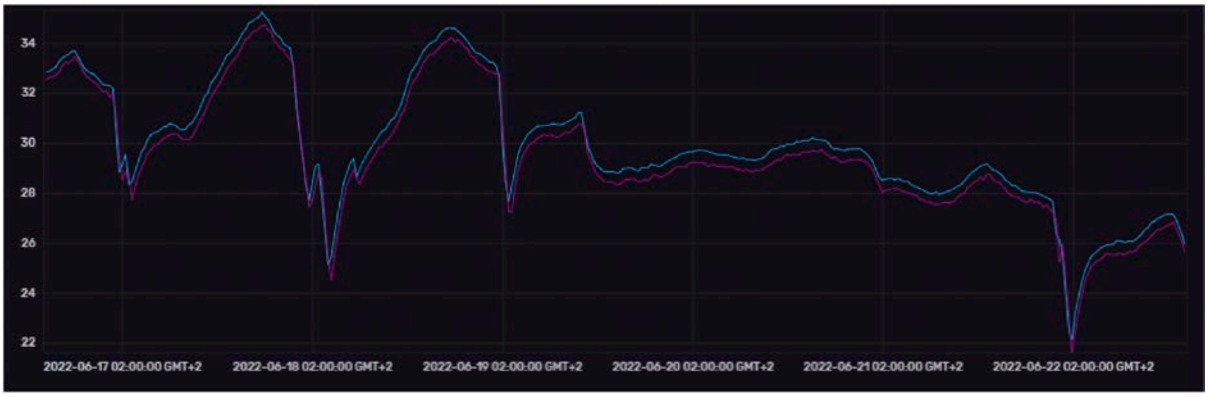

Fig. 16. InfluxDB visualization of parameters (temperatures) measured by the monitoring system located in Getafe.

Table 4
Budget for the IoT-based application for EP (Datalogger).

Component	Price [€]
1 x Open-source platform	7.60
1 x Li- battery 3,6V	6.75
1 x battery holder	4.5
1 x CO2 sensor	19.48
1 x Temperature-humidity sensor	6.40
1 x Temperature-humidity-pression sensor	3.996
1x Light sensor	2.80
Electronic components (connectors, regulators, ADCs, etc.)	14.99
1 x Electrical enclosure box, 155 × 95 × 60 mm, IP54	17.30
PCB	6.53
Total	**90.346**

for obtaining low errors in measurement and extending the long-life of the battery. Redundant sensors of the key parameters for identifying EP (air temperature and air relative humidity) have been integrated for avoiding the loss of data in case of sensors failure.

The relationship between Internet Poverty and EP has been studied determining the selection of the communication technology because of in the presence of EP, the probability of suffering Internet Poverty is higher. The communication system has been designed by combining two wireless technologies: Wi-Fi and mobile communications. This communication model allows to install individual datalogger and create small networks without including changes. Mobile communications have been used for accessing Internet (communications node) and the dataloggers communicate with the communication node by using Wi-Fi. Several dataloggers located close enough could share a unique communication node reducing costs. On the other hand, if the home to be monitored has Wi-Fi network, the IoT-based system could be connected directly to this network (without using any communications node). In case telecommunication infrastructure is not available, the system would also transmit data through mobile communications. This communication system would allow to digitize houses giving access to Wi-Fi and combating energy poverty and internet poverty at the same time. The final cost of the entire system is less than 140 euros. If the communication node is not required, the new prototype's total cost, including sensing and connectivity, is around 91 euros. The system first pilot was installed in Getafe and results showed that the datalogger is accurate, highly reliable and totally power independent.

Author contribution statement

Ascensión López Vargas; Agapito Ledezma Espino: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed reagents, materials, analysis tools or data; Wrote the paper.

Funding statement

This work was supported by the European Commission through Urban Innovative Actions of the EPIU Getafe Project under Grant UIA04-212. The work of Dr. Agapito Ledezma was supported by the Agencia Estatal de Investigación (AEI) under Grant PID2021-124335OB-C22.

Data availability statement

The authors do not have permission to share data.

Declaration of interest's statement

The authors declare no competing interests.

Acknowledgments

The authors acknowledge the support provided by Ernesto García Ares and Agustin Pulido Domínguez, Technical Staff from the CAI's Manufacturing and Design Office of the University Carlos III of Madrid. The authors acknowledge the support provided by the Healthy Households' Office service (OHS) in Getafe and the Group of Appropriate Technologies for Sustainable Development of the University Carlos III of Madrid.

References

[1] European comission website [Online]. Available: https://energy.ec.europa.eu/topics/markets-and-consumers/energy-consumer-rights/energy-poverty_en.
[2] Energy poverty advisory hub website [Online]. Available: https://www.energypoverty.eu/about/what-energy-poverty.
[3] Alfonso Carfora, Giuseppe Scandurra, Antonio Thomas, Forecasting the COVID-19 effects on energy poverty across EU member states, Energy Pol. 161 (2021), 112597, https://doi.org/10.1016/j.enpol.2021.112597 [Online].
[4] Willem Hove, Francesco Dalla Longa, Bob Zwaan, Identifying predictors for energy poverty in Europe using machine learning, Energy Build. 264 (2022), 112064, https://doi.org/10.1016/j.enbuild.2022.112064 [Online].
[5] Eutostat. https://ec.europa.eu/eurostat/web/products-eurostat-news/-/ddn-20211105-1#:~:text=An%20EU%2Dwide%20survey%20concluded,keep%20their%20home%20adequately%20warm [Online].
[6] Steve Pye, Audrey Dobbins, Claire Baffert, Jurica Brajkovic, Rocco Miglio, Paul Deane, Energy Poverty and Vulnerable Consumers in the Energy Sector across the EU: Analysis of Policies and Measures, 2015 [Online].
[7] Haitao Chen, Bin Zhang, Zhaohua Wang, Hidden inequality in household electricity consumption: measurement and determinants based on large-scale smart meter data, China Econ. Rev. 71 (2021), 101739, https://doi.org/10.1016/j.chieco.2021.101739 [Online].
[8] Fiona Shirani, Christopher Groves, Karen Henwood, Nick Pidgeon, Erin Roberts, 'I'm the smart meter': perceptions of smart technology amongst vulnerable consumers, Energy Pol. 144 (2020), 111637, https://doi.org/10.1016/j.enpol.2020.111637 [Online].
[9] M.J. Page, J.E. McKenzie, P.M. Bossuyt, et al., The PRISMA 2020 statement: an updated guideline for reporting systematic reviews, Syst. Rev. 10 (2021) 89, https://doi.org/10.1186/s13643-021-01626-4 [Online].
[10] Hossein Motlagh, Naser, Mahsa Mohammadrezaei, Julian Hunt, Behnam Zakeri, Internet of things (IoT) and the energy sector, Energies 13 (2020) 494, https://doi.org/10.3390/en13020494 [Online].
[11] S. M. d. i. t. E. Union. https://ses.jrc.ec.europa.eu/smart-metering-deployment-european-union#:~:text=To%20date%2C%20Member%20States%20have,will%20have%20one%20for%20gas [Online].
[12] P. Fergus, C. Chalmers, Energy sobriety: a behaviour measurement indicator for fuel poverty using aggregated load readings from smart meters, in: S. Ploix, M. Amayri, N. Bouguila (Eds.), Towards Energy Smart Homes, Springer, Cham, 2021 [Online].

[13] William Hurst, A. Casimiro, Curbelo Montanez, Shone Nathan, Towards an approach for fuel poverty detection from gas smart meter data using decision tree learning, in: Proceedings of the 2020 3rd International Conference on Information Management, 2020 [Online].
[14] William Hurst, Casimiro Curbelo Montañez, Nathan Shone, Dhiya Al-Jumeily Obe, An Ensemble Detection Model Using Multinomial Classification of Stochastic Gas Smart Meter Data to Improve Wellbeing Monitoring in Smart Cities, IEEE Access, 2020 [Online].
[15] M. Kochański, K. Korczak, T. Skoczkowski, Technology innovation system analysis of electricity smart metering in the European union, Energies 13 (2020) 916, https://doi.org/10.3390/en13040916 [Online].
[16] J. Ortiz, M. Jiménez Martínez, A. Alegría-Sala, S. Tirado-Herrero, I. González Pijuan, M. Guiteras Blaya, L. Canals Casals, Tackling energy poverty through collective advisory assemblies and electricity and comfort monitoring campaigns, Sustainability (2021) [Online].
[17] G.M. Huebner, I. Hamilton, Z. Chalabi, D. Shipworth, T. Oreszczyn, Comparison of indoor temperatures of homes with recommended temperatures and effects of disability and age: an observational, cross-sectional study, 2018, BMJ Open 8 (2018), e021085, 10.1136/[Online].
[18] A. Pollard, T. Jones, S. Sherratt, R.A. Sharpe, Use of simple telemetry to reduce the health impacts of fuel poverty and living in cold homes, Int. J. Environ. Res. Publ. Health 16 (2019) 2853, https://doi.org/10.3390/ijerph16162853 [Online].
[19] M. Arnesano, et al., An IoT Solution for Energy Management at Building and District Level, in: 2018 14th IEEE/ASME International Conference on Mechatronic and Embedded Systems and Applications (MESA), 2018, pp. 1–7, https://doi.org/10.1109/MESA.2018.8449168 [Online].
[20] S. Cong, D. Nock, Y.L. Qiu, et al., Unveiling hidden energy poverty using the energy equity gap, Nat. Commun. 13 (2022) 2456, https://doi.org/10.1038/s41467-022-30146-5 [Online].
[21] Shu Tang, Dennis Shelden, Charles Eastman, Pishdad-Bozorgi, Pardis, Gao, Xinghua, A Review of Building Information Modeling (BIM) and the Internet of Things (IoT) Devices Integration: Present Status and Future Trends, Automation in Construc, 2019 [Online].
[22] Hogares Saludables website. https://hogaressaludables.getafe.es/en/ [Online].
[23] Ergonomics of the Thermal Environment - Analytical Determination and Interpretation of Thermal Comfort Using Calculation of the PMV and PPD Indices and Local Thermal Comfort Criteria (ISO 7730:2005)," [Online]. https://www.iso.org/standard/39155.html.
[24] B.W. Olesen, K.C. Parsons, Introduction to thermal comfort standards and to the proposed new version of EN ISO 7730, Energy Build. 34 (2002) 537–548, https://doi.org/10.1016/S0378-7788(02)00004-X [Online].
[25] ASHRAE STANDARD 55 – thermal environmental conditions for human occupancy,"[Online]. https://www.ashrae.org/technical-resources/bookstore/standard-55-thermal-environmental-conditions-for-human-occupancy.
[26] Energy follow up survey: final report. [Online] https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/1018737/efus-fuel-poverty.pdf.
[27] ANSI/ASHRAE Standard 62.1. Ventilation for Acceptable Indoor Air Quality, 2019. https://www.ashrae.org/technical-resources/bookstore/standards-62-1-62-2.
[28] ISO/TC 159/SC 5 "Ergonomics of the physical environment"," [Online]. https://www.iso.org/committee/53390.html.
[29] Siddharth Sareen, Harriet Thomson, Sergio Tirado-Herrero, João Gouveia, Ingmar Lippert, Aleksandra Lis, European energy poverty metrics: scales, prospects and limits, Global Trans. 2 (2020) 26–36, https://doi.org/10.1016/j.glt.2020.01.003 [Online].
[30] R. Jevons, C. Carmichael, A. Crossley, A. Bone, Minimum indoor temperature threshold recommendations for English homes in winter - a systematic review, Public Health 136 (2016), https://doi.org/10.1016/j.puhe.2016.02.007 [Online].
[31] S. Tham, Ross Thompson, O. Landeg, K. Murray, T. Waite, Indoor temperature and health: a global systematic review, Public Health 179 (2019) 9–17, https://doi.org/10.1016/j.puhe.2019.09.005 [Online].
[32] Lullaby trust website. https://www.lullabytrust.org.uk/safer-sleep-advice/baby-room-temperature/ [Online].
[33] A.V. Arundel, E.M. Sterling, J.H. Biggin, T.D. Sterling, Indirect health effects of relative humidity in indoor environments, Environ. Health Perspect. 65 (1986 Mar) 351–361, https://doi.org/10.1289/ehp.8665351. PMID: 3709462; PMCID: PMC1474709.," [Online].
[34] d. i. i. a. NCCEH Website, especially%20in%20poorly%20ventilated%20rooms.," [Online], https://ncceh.ca/documents/field-inquiry/carbon-dioxide-indoor-air#:~:text=The%20average%20outdoor%20air%20concentration,.
[35] Oluwapelumi Osibona, Bethlehem Solomon, Daniela Fecht, Lighting in the home and health: a systematic review, Int. J. Environ. Res. Publ. Health 18 (2021) 609, https://doi.org/10.3390/ijerph18020609. " [Online].
[36] William Gough, Ana Zaknic-Catovic, Andrew Zajch, Sampling frequency of climate data for the determination of daily temperature and daily temperature extrema, Int. J. Climatol. 40 (2020), https://doi.org/10.1002/joc.6528. " [Online].
[37] e. a. s. s. -. h. a. i. Eurostat Website [Online], https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Digital_economy_and_society_statistics_-_households_and_individuals#Internet_access.
[38] i. p. Brookings Website. https://www.brookings.edu/blog/future-development/2021/07/26/measuring-internet-poverty/ [Online].
[39] Shangrui Wang, Anran Cao, Guohua Wang, Yiming Xiao, Impact of energy poverty on the digital divide: mediating effect of depression and Internet perception, Technol. Soc. (2022), https://doi.org/10.1016/j.techsoc.2022.101884 [Online].
[40] o. C. R. o. o. E. p. n. l. w. e. Euronews Website [Online], https://www.euronews.com/2020/11/28/residents-of-canada-real-one-of-europe-s-poorest-neighbourhoods-living-without-electricity.
[41] T. S. o. M. I. C. 2. GSMA Website [Online], gsma.com/r/wp-content/uploads/2021/09/The-State-of-Mobile-Internet-Connectivity-Report-2021.pdf.
[42] Marek Babiuch, Petr Foltynek, Pavel Smutný, Using the ESP32 Microcontroller for Data Processing, 2019, pp. 1–6, https://doi.org/10.1109/CarpathianCC.2019, 8765944.," [Online].
[43] MCP3202 datasheet. https://www.mouser.es/datasheet/2/268/21034F-64776.pdf [Online].
[44] EEMB battery website. https://www.eemb.com/model/er26500.html [Online].
[45] Bosch website. https://www.bosch-sensortec.com/products/environmental-sensors/humidity-sensors-bme280/ [Online].
[46] DHT11 datasheet. http://www.datasheet-pdf.com/PDF/DHT11-Datasheet-Aosong-785591 [Online].
[47] DHT22 datasheet. https://www.sparkfun.com/datasheets/Sensors/Temperature/DHT22.pdf [Online].
[48] López Vargas, Ascensión, M. Fuentes, Marta Vivar, Evaluation of long-term performance of a solar home system (SHS) monitoring system on harsh environments, Sensors 19 (2019), https://doi.org/10.3390/s19245462. " [Online].
[49] Canals Casals, Lluc, Sergio & Barbero Tirado-Herrero, Mattia, Corchero, Cristina, Smart Meters Tackling Energy Poverty Mitigation: Uses, Risks and Approaches, 2020, https://doi.org/10.1109/EPEC48502.2020.9320062 [Online].
[50] Cubiq website. https://en.gassensor.com.cn/ [Online].
[51] Rohm semiconductors. https://www.rohm.com/ [Online].
[52] InfñuxDB website. https://www.influxdata.com/ [Online].
[53] DB engines ranking. https://db-engines.com/en/ranking/time+series+dbms [Online].
[54] Climate data website. https://es.climate-data.org/europe/espana/comunidad-de-madrid/getafe-885499/. " [Online].
[55] Getafe municipality website. https://www.getafe.es/getafe-amplia-a-649-las-viviendas-que-seran-rehabilitadas-con-las-arru-en-las-margaritas-y-la-alhondiga/ [Online].
[56] EMSV website. https://emsvgetafe.org/servicios/rehabilitacion/areas-de-regeneracion-y-renovacion-urbana-en-getafe/ [Online].
[57] European comission website. https://ec.europa.eu/energy/sites/ener/files/documents/spain_en_version.pdf [Online].
[58] Urban innovative actions website. https://www.uia-initiative.eu/en [Online].
[59] Reuters website. https://www.reuters.com/world/europe/spain-melts-under-earliest-heat-wave-over-40-years-2022-06-13/ [Online].
[60] López Vargas, Ascensión, M. Fuentes, Marta Vivar, Current challenges for the advanced mass scale monitoring of Solar Home Systems: a review, Renew. Energy 163 (2020) 2098–2114, https://doi.org/10.1016/j.renene.2020.09.111.

Update

Heliyon

Volume 9, Issue 3, March 2023, Page

DOI: https://doi.org/10.1016/j.heliyon.2023.e14128

Heliyon 9 (2023) e14128

Contents lists available at ScienceDirect

Heliyon

journal homepage: www.cell.com/heliyon

Corrigendum

Corrigendum to “IoT application for energy poverty detection based on thermal comfort monitoring” [Heliyon 9 (1) (January 2023) Article e12943]

Ascensión López-Vargas *, Agapito Ledezma-Espino

Control Learning and Optimization Group, Computer Science and Engineering Department, University Carlos III of Madrid. Leganes, Madrid, Spain

In the original published version of this article, the funding information was incomplete. The authors have now updated the funding information. *The correct version of the* funding *information can be found below*:

The work of Dr. Agapito Ledezma was supported by Grant PID2021-124335OB-C22 funded by MCIN/AEI 10.13039/501100011033 and by the European Union.

The authors apologize for the errors. Both the HTML and PDF versions of the article have been updated to correct the errors.

Declaration of interests statement

The authors declare no conflict of interest.

DOI of original article: https://doi.org/10.1016/j.heliyon.2023.e12943.

* Corresponding author.
E-mail address: aslopezv@inf.uc3m.es (A. López-Vargas).

https://doi.org/10.1016/j.heliyon.2023.e14128
Received 22 February 2023; Accepted 22 February 2023
Available online 28 February 2023
2405-8440/